

## **Gig Economy as a Matching Shock in Agriculture**

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### **Abstract**

This study reconceptualizes Indonesia's agricultural labor market as a dual internal economy comprising a traditional on-farm segment and a modern upstream–downstream agribusiness sector, each characterized by distinct search and matching frictions. Building on the Mortensen–Pissarides framework, we model the digital gig economy as a technological shock that enhance the job-matching efficiency parameter within the traditional segment. Using a Monte Carlo equilibrium simulation (10,000 draws) calibrated with Indonesian labor statistics, the study evaluates counterfactual scenarios representing 10–50% improvements in matching efficiency to simulate progressive digital diffusion. Results indicate that improved matching efficiency can reduce aggregate unemployment by 0.3–1.0 percentage points, create over 300,000 additional jobs, and increase agricultural GDP by up to 1.8%. Approximately 70–90% of these gains originate from on-farm employment, while the remainder reflects spillovers to modern agribusiness through induced demand and digital linkages. Sensitivity analysis underscores that sectoral composition and spillover elasticity shape the magnitude of macroeconomic gains. Conceptually, the study integrates labor-market frictions into theories of technological diffusion and structural change. As a simulation-based theoretical experiment, it offers a plausible framework for understanding how gig platforms can function as transitional accelerators of inclusive rural transformation.

**Keywords:** dual-sector model, matching efficiency, agricultural transformation, welfare dynamics, employment absorption.

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### **1. Introduction**

The global rise of the digital gig economy is reshaping how labor is organized, governed, and remunerated. Initially concentrated in urban services such as ride-hailing and delivery (Huda et al., 2024; De Stefano, 2016; Graham et al., 2017;), gig work now represents more than flexible freelance labor, it constitutes a digitally coordinated system that algorithmically matches labor supply and demand. This coordination function has begun to diffuse into agriculture, transforming how workers, tasks, and production cycles are connected across space and time (Kuhn & Maleki, 2017; Wood., 2019).

Across developing economies, emerging agri-gig platforms such as TROTRO Tractor in Ghana, Hello Tractor in Nigeria, Tun Yat in Myanmar, and Koltiva in Indonesia demonstrate how digital matching systems can organize seasonal or on-demand agricultural work, optimize mechanization services, and facilitate logistics and traceability (FAO, 2024; World Bank, 2023; Foster & Heeks, 2023). These examples show that digital coordination is no longer confined to urban services but increasingly embedded in rural production systems, where it reduces transaction costs, enhances labor mobility, and mitigates coordination failures.

Globally, agriculture still employs nearly 28% of the workforce, predominantly under informal or semi-formal arrangements (ILO, 2023). Yet rural productivity decline and demographic aging coexist with rising urban youth unemployment, reflecting not merely a wage gap but a coordination failure between labor supply and demand. In Indonesia, where agriculture employs 38.99 million workers (26,75% of the labor force) but contributes only 10.52% to GDP (BPS, 2025; Pusdatin, 2025), such mismatches persist despite ongoing modernization efforts. These patterns reveal a persistent structural gap: labor-market efficiency, not just productivity, is a critical constraint in agricultural transformation.

This study conceptualizes Indonesia's agricultural labor system as a dual internal economy comprising two interdependent segments with asymmetric frictions: (1) a traditional on-farm sector, labor-intensive and characterized by high search costs, limited mobility, and diminishing returns; and (2) a modern upstream–downstream agribusiness sector, capital- and technology-intensive yet constrained by input bottlenecks and skilled-labor shortages (Timmer, 2015; McCullough, 2017; Klerkx & Rose, 2020). Rather than treating these as separate domains, the dual internal economy represents a continuum of production relations within agriculture, from cultivation to processing, logistics, and marketing linked by digital coordination. Within this structure, platform-based gig systems function as connectors that enhance matching efficiency between labor supply and demand across segments. This mechanism enables the reabsorption of underemployed rural workers and, over time, the re-entry of urban labor into productive agricultural activities.

This reinterpretation extends the Lewis (1954) and Ranis–Fei (1961) models of structural transformation. Whereas mid-twentieth-century development involved shifting labor out of agriculture into industry, contemporary transformation especially in economies like Indonesia can occur within agriculture itself through the growth of agro-industrial and service linkages. When gig platforms institutionalize digital coordination, they can raise the productivity frontier of traditional agriculture and strengthen its integration with modern agribusiness. In doing so, the classical Lewis turning point becomes an internal inflection point, where digital coordination enhances labor matching, stabilizes rural wages, and fosters inclusive productivity gains.

The analytical foundation builds on the Mortensen–Pissarides theory of search and matching, which explains how employment levels depend on the efficiency of worker–vacancy matching under frictional constraints (Mortensen & Pissarides, 1994; Hall & Schulhofer-Wohl, 2018). Within this framework, gig platforms act as positive shocks to matching efficiency ( $\mu$ ), thereby reducing equilibrium unemployment and improving labor utilization. In a dual internal economy, efficiency gains in the traditional segment generate productivity spillovers into modern agribusiness through

enhanced coordination, logistics, and value-chain linkages. This mechanism mitigates both frictional unemployment by accelerating job matching and structural unemployment by aligning skills with emerging digital demands (ILO, 2023; Nambisa et al., 2019).

Methodologically, a Monte Carlo equilibrium simulation is calibrated to Indonesia's 2025 labor data, with parameters validated using 2015–2025 labor-market trends. The analysis constitutes a simulation-based theoretical experiment linking search–matching dynamics with the structural logic of dual-sector transformation.

Beyond its modeling contribution, the paper advances a normative argument: that when supported by labor protection, wage regulation, and digital inclusion, the gig economy can evolve from a precarious work arrangement into a transitional coordination system that stabilizes income, reduces inequality, and attracts urban labor back into agriculture (Huda et al., 2021; Joo & Shawl, 2021; Khethisa et al., 2020; Tan et al., 2021; Kurin, 2016). Under such conditions, agriculture can transition from a residual employment reservoir into a coordinated, multi-nodal system spanning input supply, processing, logistics, and marketing. Platformization thus represents structured flexibility rather than informality, where digital coordination complements rather than replaces formal employment systems (Christiansen et al., 2020; Rochaeni, 2023; Thaba, 2025; Festus et al., 2016; Osabohien et al., 2019; Dzingirai, 2021).

This study contributes to three strands of debate. First, it extends dual-economy and search–matching models to account for digital coordination in segmented rural markets. Second, it offers a calibrated framework for assessing how platform-mediated efficiency improvements influence employment and output. Third, it enriches policy debates by positioning the gig economy as a transitional accelerator of inclusive agricultural transformation conditional upon complementary institutional innovations, digital infrastructure, portable social protection, and adaptive labor regulation.

## 2. Research method

### 2.1. Data and Sources

This study employs a structural calibration and stochastic simulation approach to estimate the potential macro-labor effects of digital and gig-based platforms on Indonesia's agricultural sector. All baseline parameters are drawn from official and internationally recognized datasets.

The total number of agricultural workers (38.99 million) and the national unemployment rate (4.76%) are obtained from the Survei Angkatan Kerja Nasional (Sakernas) published by Badan Pusat Statistik (BPS, 2025). Sectoral employment shares are based on FAO (2023) and World Development Indicators (World Bank, 2024). These proportions form the empirical foundation of the dual-sector model.

The baseline calibration reproduces Indonesia's 2025 agricultural labor equilibrium, serving as a reference point against which counterfactual digitalization scenarios are simulated. Historical

unemployment trends for 2015–2025 are also used to validate the realism of the assumed parameter ranges, ensuring internal consistency between model-predicted and observed macro-labor aggregates.

## 2.2. Model Structure and Equilibrium Logic

The analytical framework adapts the Mortensen–Pissarides (1994) search-and-matching model to a dual internal economy comprising: (1) traditional (on-farm) agriculture, representing smallholder and seasonal activities with high frictions and limited digital penetration (2) modern (non-farm) agribusiness, encompassing upstream (input supply, mechanisation services) and downstream (logistics, processing, marketing) segments that already exhibit some digitalisation. Each sub-sector features a matching function form:

$$m_i(v_i, u_i) = \mu_i v_i^{\alpha_1} u_i^{1-\alpha_1}, i \in \{T, M\} \quad (1)$$

where  $v_i$  is the number of vacancies,  $u_i$  the unemployed workers,  $\mu_i$  the matching-efficiency parameter, and  $\alpha_1$  the elasticity of vacancies.

The gig economy is modeled as a technological shock that raises the matching-efficiency parameter ( $\mu_i$ ) in the traditional sector, reflecting the introduction of digital platforms that improve labor coordination and reduce search frictions. In equilibrium, a higher  $\mu$  reduces the steady-state unemployment rate ( $u^*$ ) and increases labor utilization:

$$u_i^* = \frac{s_i}{s_i + \mu_i \theta_i^{\alpha_i}}, \quad (2)$$

where  $s_i$  is the job-separation rate and  $\theta_i = \frac{v_i}{u_i}$  is labour-market tightness.

Because direct microdata on vacancies and matching efficiency are unavailable, these latent parameters are inferred indirectly through equilibrium identities linking unemployment, job-finding, and separation rates an approach standard in macro-labor modeling (Petrongolo & Pissarides, 2001; Hall & Schulhofer-Wohl, 2018). In steady-state equilibrium ( $E = 0$ ), the unemployment rate ( $u^*$ ) satisfies:

$$u^* = \frac{s}{s + \mu \theta^{1-\alpha}} = \frac{s}{s + f} \quad (3)$$

Where  $s$  is the separation rate. Equivalently, given an observed steady-state unemployment rate  $u$ , the implied job-finding rate is:

$$f = s \left( \frac{1-u}{u} \right) \quad (4)$$

### 2.3. Calibration and Parameter Ranges

Table 1 presents the calibration values and their empirical or theoretical bases. Parameter ranges are derived from international studies of labor-market frictions in developing and rural economies, ensuring plausibility and internal coherence.

Calibration ensures that steady-state unemployment in the baseline scenario matches Indonesia's 2025 aggregate value. Parameter uncertainty is addressed through stochastic sampling over these ranges.

**Table 1.** Summarize of Calibartion Values and Sources

| Parameter                         | Symbol                 | Value/Rang<br>e | Source/Rationale                                                                        |
|-----------------------------------|------------------------|-----------------|-----------------------------------------------------------------------------------------|
| Separation rate (traditional)     | $s_t$                  | 0.02–0.06       | Seasonal turnover in rural labor markets (Silva & Toledo, 2009)                         |
| Separation rate (modern)          | $s_m$                  | 0.01–0.04       | Lower turnover in formal agribusiness operations.                                       |
| Matching elasticity (vacancies)   | $\alpha_i$             | 0.6–0.8         | Standard elasticity range (Petrongolo & Pissarides, 2001).                              |
| Matching efficiency (traditional) | $\mu_t$                | 0.8–1.0         | Calibrated to reproduce baseline unemployment; moderate rural efficiency.               |
| Matching efficiency (modern)      | $\mu_m$                | 0.9–1.2         | Higher due to infrastructure and connectivity advantages.                               |
| Sectoral labor shares             | $\lambda_t, \lambda_m$ | 0.80, 0.20      | Indonesia's agricultural employment structure (BPS, 2024; FAO, 2023; World Bank, 2024). |

Source: Process

### 2.4. Empirical Validation Using Unemployment Trends

To ensure that the simulated improvements in matching efficiency ( $\mu$ ) reflect plausible magnitudes, this study incorporates a descriptive validation using Indonesia's unemployment time series for 2015–2025 (BPS, 2025).

**Table 2.** Derived Job-Finding Probabilities from Indonesia's Unemployment Trends (2015-2025)

| Year | Unemployment Rate (u, %) | Labor force (L, million) | Implied job-finding rate (f) |
|------|--------------------------|--------------------------|------------------------------|
| 2015 | 6.18                     | 114.8                    | 0.53                         |
| 2016 | 5.61                     | 118.4                    | 0.67                         |
| 2017 | 5.50                     | 121.0                    | 0.68                         |
| 2018 | 5.30                     | 126.3                    | 0.71                         |
| 2019 | 5.23                     | 128.8                    | 0.72                         |
| 2020 | 7.07                     | 128.5                    | 0.52                         |
| 2021 | 6.49                     | 131.1                    | 0.57                         |
| 2022 | 5.86                     | 135.3                    | 0.64                         |
| 2023 | 5.32                     | 139.9                    | 0.71                         |
| 2024 | 4.82                     | 144.6                    | 0.79                         |
| 2025 | 4.76                     | 145.8                    | 0.80                         |

Source: Process (Job-finding rate (f) calculated as  $f = s(1 - u)/u$ , with constant rate (s) = 0.04

During this period, the national unemployment rate declined from **6.18% in 2015** to **4.76% in 2025**, while the total labor force expanded from **114.8 million** to **145.8 million** workers. Assuming a constant annual separation rate of **s = 0.04**, the implied job-finding probability increased from **f = 0.53** in 2015 to **f = 0.80** in 2025 an approximate **50% improvement** in matching efficiency.

This historical trajectory substantiates the plausibility of the model's counterfactual scenarios, which represent incremental stages of digital diffusion in rural labor coordination. The 2015–2025 trend analysis thus functions as an empirical anchor for the simulation, ensuring that the modeled efficiency shocks are consistent with observed macro-labor dynamics rather than speculative assumptions.

## 2.5. Monte Carlo Simulation Design

Monte Carlo inference is conducted to explore the sensitivity of equilibrium outcomes to parameter variation. Each simulation iteration randomly samples from bounded uniform distributions for  $s$ ,  $\alpha$ , and  $\mu$  within their specified intervals. Uniform draws are chosen to maintain equal prior weights across feasible parameter values and avoid bias toward central estimates a common approach in structural stochastic calibration (Metropolis & Ulam, 1994).

For each draw ( $N = 10,000$ ), the model resolves steady-state equilibrium by recomputing labor-market tightness ( $\theta$ ), unemployment ( $u^*$ ), and vacancies ( $V$ ) under three counterfactual scenarios of digital adoption:

**Table 3.** Scenario simulation

| Scenario   | $\Delta\mu$ (%) | Interpretation           |
|------------|-----------------|--------------------------|
| Pesimistic | 10              | Low platform uptake      |
| Moderate   | 20              | Partial diffusion        |
| Optimistic | 50              | Full digital integration |

Source: Process

Each scenario isolates the pure effect of matching improvements by holding separation rates constant. For each simulation, median, 5th, and 95th percentiles of key outcomes (unemployment, job absorption, GDP index) are reported, providing credible intervals rather than point estimates. Aggregate output (Y) is modeled as a function of average productivity (y) and effective employment (E):

$$Y = y(1 - u^*) \quad (5)$$

Differentiating with respect to  $\mu$  yields:

$$\frac{dY}{d\mu} = -y \frac{du^*}{d\mu} > 0 \quad (6)$$

This implies that improvements in matching efficiency translate into higher output, even if productivity per worker (y) remains constant. In practical terms, when digital coordination improves the success rate of worker–vacancy matching, the resulting decline in unemployment directly increases total output and labor utilization.

## 2.6. Robustness and Empirical Plausibility

To strengthen empirical credibility, simulation outcomes are cross-validated against evidence from comparable rural digital-labor platforms. These observed magnitudes fall within the simulated effect ranges of this study, lending external plausibility to the model’s assumptions. A supplementary robustness checks replicates the simulation under alternative parameterizations: (1) normal instead of uniform random draws, and (2)  $\pm 0.5$  percentage-point deviations in baseline unemployment. Both tests confirm the direction and relative magnitude of results, indicating that findings are not sensitive to specific distributional or baseline choices

## 2.7. Computational Procedure and Limitations

Simulations are implemented in Stata 17 using parallelized Monte Carlo routines to ensure computational efficiency. Results are summarized using percentile-based uncertainty intervals. While the method is theoretically grounded, it has intrinsic limitations. It relies on calibrated rather than econometrically estimated parameters and lacks microdata on job search behavior or wage differentials. Hence, results should be interpreted as plausible ranges of effect, not precise forecasts. Nonetheless, the approach provides a transparent, reproducible framework that bridges theoretical modeling and policy relevance illustrating how digital coordination could reshape labor allocation and productivity within Indonesia’s dual agricultural system.

### 3. Results and Discussion

#### 3.1. Aggregate Effects of Improved Matching Efficiency

Table 4 reports the simulated aggregate outcomes under alternative values of the matching-efficiency parameter ( $\mu$ ). The baseline replicates Indonesia's 2025 agricultural equilibrium, with unemployment at 4.76 % and 1.58 million vacancies. Increasing  $\mu$  by 10–50 % produces a monotonic decline in unemployment, reaching 3.74 % in the most optimistic scenario a reduction of 1.02 percentage points, equivalent to roughly **398,000 additional jobs**.

**Table 4.** Aggregate Impact of Improved Job-Matching Efficiency in Agriculture

| Scenario                           | Market Tightness ( $\theta$ ) | Unemployment Rate (%) | Change in Unemployment Rate (pp) | Employment Absorption (persons) | Vacancies (million) |
|------------------------------------|-------------------------------|-----------------------|----------------------------------|---------------------------------|---------------------|
| Baseline                           | 0.853                         | 4.76                  |                                  |                                 | 1.583               |
| +10% Matching Efficiency ( $\mu$ ) | 0.779                         | 4.30                  | −0.46                            | 181,089                         | 1.293               |
| +20% Matching Efficiency ( $\mu$ ) | 0.708                         | 4.13                  | −0.63                            | 245,168                         | 1.126               |
| +50% Matching Efficiency ( $\mu$ ) | 0.563                         | 3.74                  | −1.02                            | 397,737                         | 0.800               |

Source: Process

These reductions reflect a pronounced tightening of the labor market: vacancies contract by nearly half as digital coordination accelerates worker–firm matching and shortens search durations. This pattern aligns with the theoretical predictions of Mortensen and Pissarides (1994) and subsequent refinements by Hall and Schulhofer-Wohl (2018), who show that increases in  $\mu$  elevate match probabilities and compress equilibrium unemployment.

Comparable empirical evidence strengthens the plausibility of these magnitudes. Digital job-matching platforms in India and Vietnam reduced rural unemployment by 1–1.5 percentage points and decreased average search times by 25–40 % (Du et al., 2023; Nguyen & Pascual, 2023). Kenya's mobile-based labor exchanges similarly lowered idle time and raised productivity by 12 % (Foster & Heeks, 2023). Indonesia's own pilot farmer-platform initiatives suggest comparable potential once scaled nationally (World Bank, 2023).

However, these aggregate gains obscure significant **institutional and social constraints**. Improvements in  $\mu$  presuppose the expansion of digital literacy, reliable data infrastructures, and adaptive regulatory frameworks conditions that remain unevenly distributed across Indonesia. Without targeted interventions, digital improvements may exacerbate existing divides: workers with higher education, better connectivity, or stronger social networks are more likely to benefit, while marginalized groups particularly women and informal workers risk exclusion (ASEAN Secretariat, 2024; Chen, 2016; Rao, 2022).

Thus, although aggregate unemployment declines, the distribution of benefits may remain unequal. Gig platforms can enhance access and flexibility, but they may also introduce new forms of precarity if institutional safeguards lag behind technological change. Ensuring inclusive outcomes requires a complementary policy agenda encompassing digital capacity-building, interoperable data governance, and labor-rights protections suited to flexible platform-based work.

### 3.2. Sectoral Dynamics-Traditional and Modern Agriculture

Table 5 disaggregates the effects across agricultural sub-sectors. Consistent with employment shares, the traditional on-farm segment generates the largest absolute job gains up to **353,000 workers** under a 50 % increase in  $\mu$ . The modern agro-industrial sector exhibits smaller absolute gains, but relatively larger proportional improvements, with unemployment falling from 4.76 % to 4.28 %.

**Table 5.** Sectoral Impact of Job-Matching Efficiency Improvement

| Scenario                            | Market Tightness ( $\theta$ ) | Unemployment Rate (%) | Employment Absorption (persons) | Vacancies (million) |
|-------------------------------------|-------------------------------|-----------------------|---------------------------------|---------------------|
| <b>Traditional (on-farm)</b>        |                               |                       |                                 |                     |
| Baseline                            | 0.850                         | 4.76                  | -                               | 1.262               |
| +10% Matching Efficiency ( $\mu$ )  | 0.742                         | 4.28                  | 149,108                         | 0.985               |
| +20% Matching Efficiency ( $\mu$ )  | 0.655                         | 4.10                  | 207,505                         | 0.829               |
| +50% Matching Efficiency ( $\mu$ )  | 0.476                         | 3.63                  | 352,856                         | 0.533               |
| <b>Modern (upstream-downstream)</b> |                               |                       |                                 |                     |
| Baseline                            | 0.851                         | 4.76                  | -                               | 0.316               |
| +10% Matching Efficiency ( $\mu$ )  | 0.827                         | 4.45                  | 24,087                          | 0.286               |

| Scenario                              | Market<br>Tightness ( $\theta$ ) | Unemployment<br>Rate (%) | Employment<br>Absorption<br>(persons) | Vacancies<br>(million) |
|---------------------------------------|----------------------------------|--------------------------|---------------------------------------|------------------------|
| +20% Matching<br>Efficiency ( $\mu$ ) | 0.805                            | 4.41                     | 27,495                                | 0.276                  |
| +50% Matching<br>Efficiency ( $\mu$ ) | 0.742                            | 4.28                     | 37,526                                | 0.247                  |

Source: Process

This asymmetric response mirrors empirical patterns observed by Cazzuffi and Moratti (2021) and de Vries et al. (2021): early stages of digital diffusion disproportionately benefit labor-intensive segments by reducing information frictions and improving task coordination, whereas capital-intensive segments reap productivity gains only at later stages. These dynamics correspond to Christiaensen and Premand's (2022) "dual-acceleration" hypothesis, where digital adoption enhances both job absorption (quantity) and allocation efficiency (quality).

The results also resonate with a modernized Lewis–Ranis–Fei perspective. Instead of labor reallocation via rural–urban migration, **digital coordination within agriculture itself** drives the productivity-enhancing transitions (Timmer, 2015; Rizov & Swinnen, 2016). In this sense, platform-mediated work becomes a mechanism of *in-situ* structural transformation.

Yet these potential benefits are highly contingent on institutional capacity. Connectivity gaps, fragmented rural data systems, limited algorithmic transparency, and weak enforcement of labor standards can all limit or distort platform effects (OECD, 2024). Moreover, extensive research on the gig economy warns of risks such as income instability, weak bargaining power, and opaque rating systems (Rao, 2022; Wood et al., 2019). These risks may be magnified in agriculture, where work is already seasonal, weather-dependent, and structurally informal.

Accordingly, digital labor platforms must be recognized not merely as technological tools but as institutional systems that structure power, risk, and access within labor markets. Their positive contribution to Indonesia's rural transformation hinges on governance arrangements that align flexibility with fairness through clear standards for data use, transparent matching algorithms, and social-protection mechanisms adapted to intermittent agricultural work.

### 3.3. Robustness and Spillover Effects Across Sectors

Table 6 presents robustness checks incorporating alternative sectoral compositions and spillover coefficients ( $\gamma$ ). As  $\gamma$  increases, both employment and output gains expand markedly. Under an 80:20 traditional-to-modern split, increasing  $\gamma$  from 0 to 0.5 reduces unemployment from 4.65 % to 4.54 % (around 42,000 jobs). With a 60:40 composition, strong spillovers yield **147,000 additional jobs** and a GDP index rise to **1.0189**.

**Table 6.** Robustness-Sectoral Composition and Spillover

| Sector Share<br>(Traditional:<br>Modern) | Spillover<br>( $\gamma$ ) | Elasticity<br>( $\alpha$ ) | Unemploy<br>ment (%) | $\Delta E$<br>(‘000) | $\Delta GDP$<br>Index |
|------------------------------------------|---------------------------|----------------------------|----------------------|----------------------|-----------------------|
| 80:20                                    | 0.0                       | 0.7                        | 4.65                 | 46                   | 1.0149                |
| 80:20                                    | 0.5                       | 0.7                        | 4.54                 | 88                   | 1.0163                |
| 70:30                                    | 0.0                       | 0.7                        | 4.59                 | 63                   | 1.0155                |
| 70:30                                    | 0.5                       | 0.7                        | 4.47                 | 111                  | 1.0174                |
| 60:40                                    | 0.0                       | 0.7                        | 4.56                 | 84                   | 1.0162                |
| 60:40                                    | 0.5                       | 0.7                        | 4.38                 | 147                  | 1.0189                |
| 70:30                                    | 0.1                       | 0.6                        | 4.63                 | 58                   | 1.0150                |
| 70:30                                    | 0.1                       | 0.8                        | 4.55                 | 89                   | 1.0166                |

Source: Process

These multiplier effects reflect deep structural complementarities between the two agricultural segments. Improved coordination in the traditional sector alleviates upstream and downstream bottlenecks raising efficiency in logistics, processing, and marketing while increased agro-industrial demand stimulates higher on-farm labor absorption. This reciprocal reinforcement resembles the rural–industrial feedback loops identified by Quintana and Wenban-Smith (2020) and the cross-sector digital spillovers documented by Li et al. (2023).

The amplification mechanism operates through both supply-side channels (reduced input bottlenecks, greater labor predictability) and demand-side channels (enhanced farm-to-market linkages, greater processing throughput). In combination, these create a coordination-driven growth cycle analogous to endogenous growth dynamics in rural economies (Blythe & Tranchant, 2021).

Yet this mechanism is not automatic. Where digital infrastructure is weak, payment systems are fragmented, or data interoperability is limited, spillovers may be highly uneven. As ADB (2023) and ASEAN Secretariat (2024) emphasize, provinces with stronger connectivity and agro-industrial linkages will capture outsized gains, while lagging regions may remain locked in low-productivity equilibria. Consequently, digitalization without institutional integration risks reproducing regional inequalities rather than closing them.

### 3.4. Sensitivity to Elasticity and Institutional Flexibility

Table 7 shows how employment and output respond to variations in matching elasticity ( $\alpha$ ) and spillover intensity ( $\gamma$ ). Higher elasticity representing a more responsive firm-side adjustment to available labor substantially magnifies the effects of improved matching. Increasing  $\alpha$  from 0.6 to 0.8 (holding  $\gamma = 0.5$ ) nearly doubles the unemployment reduction, from 0.18 to 0.29 percentage points, and raises employment absorption from 72,000 to **106,000 workers**.

**Table 7.** Sensitivity-Elasticity and Spillover

| Elasticity<br>( $\alpha$ ) | Spillover<br>( $\gamma$ ) | $\Delta u$ (pp) | $\Delta E$ ('000) | $\Delta GDP$<br>Index |
|----------------------------|---------------------------|-----------------|-------------------|-----------------------|
| 0.6                        | 0.0                       | -0.11           | 42                | 1.0145                |
| 0.6                        | 0.5                       | -0.18           | 72                | 1.0158                |
| 0.7                        | 0.0                       | -0.12           | 46                | 1.0149                |
| 0.7                        | 0.5                       | -0.23           | 88                | 1.0163                |
| 0.8                        | 0.0                       | -0.15           | 59                | 1.0154                |
| 0.8                        | 0.5                       | -0.29           | 106               | 1.0171                |

Source: Process

These results echo findings by Yashiv (2007) and Hall and Petrosky-Nadeau (2016), show that elasticity shapes the speed and magnitude of labor-market adjustment to technological shocks. Empirical evidence from East Asia (Wang et al., 2022) suggests that firms capable of reorganizing tasks and reallocating workers adapt more effectively to digitalization, converting improved coordination into tangible productivity gains.

Crucially, in developing economies elasticity is not purely technological, it is **institutionally mediated**. Flexible wage-setting arrangements, transparent contracting, adaptive regulation, and worker protections determine how efficiently firms and workers can capitalize on digital platforms. Where labor markets are rigid or social protection is weak, improvements in  $\mu$  may yield diminishing or uneven returns (ILO, 2023; IFAD, 2022).

For Indonesia, increasing institutional flexibility through digital-skills training, gender-inclusive platform design, interoperable data systems, and portable social protection for gig-based agricultural workers could enhance elasticity and magnify the benefits of rural digitalization. Conversely, inadequate regulation could replicate the precarity observed in urban gig economies: unstable income streams, algorithmically mediated dependence, and erosion of bargaining power (Rao, 2022; Chen, 2016). Thus, institutional adaptation is not merely complementary but essential for converting efficiency gains into inclusive rural transformation.

### 3.5. Sectoral Comparison in Traditional and Modern Agricultural Labor Markets

Table 8 differentiates the impact of digital matching efficiency across the traditional (on-farm) and modern (agro-industry) agricultural labor markets. The results reveal two structurally distinct responses to platform-mediated coordination.

**Table 8.** Sectoral Comparison-Traditional and Modern Labor Markets

| Scenario            | Spillover ( $\gamma$ ) | Sector      | Matching Efficiency ( $\theta$ ) | Unemployment (%) | $\Delta u$ (pp) | $\Delta E$ ('000) | Sectoral GDP Index |
|---------------------|------------------------|-------------|----------------------------------|------------------|-----------------|-------------------|--------------------|
| Baseline            | 0.0                    | Traditional | 0.61                             | 5.41             | —               | —                 | 1.000              |
| Baseline            | 0.0                    | Modern      | 0.94                             | 3.98             | —               | —                 | 1.000              |
| Moderate Efficiency | 0.1                    | Traditional | 0.64                             | 5.36             | -0.05           | 18                | 1.001              |
| Moderate Efficiency | 0.5                    | Traditional | 0.72                             | 5.22             | -0.19           | 73                | 1.004              |
| Moderate Efficiency | 0.0                    | Modern      | 1.02                             | 3.83             | -0.15           | 55                | 1.007              |
| Moderate Efficiency | 0.1                    | Modern      | 1.07                             | 3.79             | -0.19           | 69                | 1.009              |
| Moderate Efficiency | 0.5                    | Modern      | 1.17                             | 3.71             | -0.27           | 96                | 1.013              |

Source: Process

The modern segment shows a more elastic reaction to improvements in matching efficiency ( $\theta$ ). Even modest increases in  $\mu$  reduce unemployment by 0.15–0.27 percentage points and generate 55,000–96,000 jobs, reflecting higher complementarities between digital coordination and capital-intensive production. This is consistent with findings by Li, Guo, and Xu (2022) and De Vries et al. (2021), who observe that digitally intensive and vertically integrated agricultural segments experience amplified gains from information symmetry, algorithmic scheduling, and real-time logistics.

The traditional on-farm sector exhibits weaker direct responsiveness to digital tools but stronger sensitivity to spillover effects. When spillover coefficients ( $\gamma$ ) rise from 0.1 to 0.5, unemployment in the traditional segment falls by 0.05–0.19 percentage points equivalent to 18,000–73,000 additional jobs. These spillovers likely operate through improved coordination with upstream–downstream activities, reduced post-harvest delays, and smoother seasonal labor reallocation. Similar cross-segment spillovers have been documented in China, India, and Ethiopia, where digital coordination in processing and logistics indirectly stabilizes rural labor demand (Christiaensen & Premand, 2022; Wang et al., 2022).

The dual response pattern demonstrates how platform-mediated gig work functions differently across agricultural substructures. The modern sector aligns with characteristics observed in global gig-

economy research high task granularity, time-sensitive workflows, and stronger algorithmic control leading to rapid matching improvements (Wood et al., 2019; Graham et al., 2017). By contrast, the traditional segment—seasonal, spatially dispersed, and informally organized—gains more through coordination chains than through direct platform engagement. This confirms earlier observations that gig platforms integrate more readily with formal or semi-formal agricultural value chains than with purely on-farm labor (Chen, 2016; Rao, 2022).

The results highlight institutional bottlenecks that mediate these sectoral differences. The weaker responsiveness of the traditional segment likely reflects lower digital literacy, inconsistent connectivity, and limited adoption incentives among smallholders conditions widely noted in ASEAN agricultural digitization assessments (ASEAN Secretariat, 2024; ADB, 2023). Gendered digital divides may also constrain women’s participation in platform-mediated rural labor, particularly in seasonal tasks where cultural norms restrict mobility (Rao, 2022; Chen, 2016). Without parallel investments in digital inclusion and labor governance, platforms may unintentionally deepen disparities even as aggregate productivity rises.

Table 8 shows that while both sectors benefit, the composition and mechanism of gains differ. Modern sector, direct efficiency gains, faster matching and continuous employment growth. Traditional sector, indirect spillover gains through smoother seasonal coordination accordingly reduced idle time. This duality underscores that platform-based gig systems do not transform agriculture uniformly; rather, they interact with existing institutional and production structures, reinforcing strengths and exposing vulnerabilities within each segment of the rural labor market.

#### 4. Conclusion and Recommendations

This study demonstrates that modest improvements in labor-market matching efficiency modeled here as a digital or gig-platform shock can enhance employment absorption, raise sectoral productivity, and generate meaningful spillovers between traditional on-farm work and the modern upstream–downstream agribusiness economy. More importantly, the research contributes methodologically by introducing a structural simulation framework capable of representing dual agricultural labor markets and their heterogeneous frictions, an area where empirical identification is often constrained by seasonality, informality, and complex rural production systems. As a simulation-based experiment, the estimates serve as indicative rather than definitive outcomes, underscoring both the potential of digital coordination mechanisms and the limits of inference in the absence of granular behavioral data. Future work should extend this framework with micro-level and longitudinal evidence, explicitly incorporate peak–off-season dynamics, and refine sectoral boundaries to better capture the institutional and technological conditions under which platform-mediated gig work can sustainably support rural transformation and national employment strategies.

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